APPLICATIONS OF TEXTURE ANALYSIS FOR ROCK TYPES DISCRIMINATION

Final [redacted] Technical Report

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Aimed at developing image processing methods for rock types analysis with LANDSAT data, numerous experiments were conducted using supervised and unsupervised classification techniques under the general concept of texture analysis with LANDSAT digital data covering two geological quads of Nevada.

The results indicate that the supervised classification method is

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very effective in the extraction of granite regions when (1) data were in ratio format, (2) feature variables included both tone and texture information, and (3) the classifier is capable of handling non-normally distributed data. Classification errors occurred when there exists pixels of non-granite category whose spectral and textural properties are statistically similar to that of granite pixels. Two cases of errors can be noted: Type 1 pixels located at the periphery of the granite regions, and Type 2 pixels located far away from the core of the granite areas.

To reduce the error rate, an unsupervised classification method based on the concept of region growing and texture clustering analysis was employed to segment the scene in multiple stages and thus depict edge patterns by the scene content and a gradual mathematical generalization process. Identification of the grantie regions becomes a labeling process using the training sets information. Since the Regions algorithm is based on an additional constraint on spatial contiguity, the above-mentioned two types of errors can be effectively reduced bacause sharp edges exist between the granite and non-granite pixels in the study area

The final decision regarding the delineation of the granite regions is based on the intersection of two classification maps using a simple map overlay analysis. The result yields a correct classification rate of about 95 percent based on a visual comparision between the composite classification map and the ground truth information given in the U.S.G.S geological map of the study area.

To improve the developed techniques for lithological analysis, it is recommended that additional experiments be conducted using other regions in the United States centering around the following tasks:

(1) developing algorithms for merging supervised and unsupervised classification methods;
(2) finetuning the Region algorithm by adding subroutings to output digital information of each segmented region;
(3) developing a color prediction model for rock types identification using the texture and tone information in the color domain with a color monitor; and
(4) developing change detection methods for monitoring purposes based on the extension of the above three methods.

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PREFACE

This research was sponsored by the Advanced Research Projects Agency under the monitorship of Mr. William Best of Air Force Office of Scientific Research. Dr. Shin-yi Hsu is the principal investigator. Research scientists of the project include Dr. Timothy Masters and Ms. Jane Huang of Susquehanna Resources and Environment, Inc.

Mr. Jack Rachlin and his associates at U.S. Geological Survey provided technical assistance and advice throughout the effort. Lt. Colonel James Smith of AFOSR also served as technical evaluator and adviser.

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Executive Summary

It has been determined in the literature on seismology and geophysics that the recorded seismic ware energy from nuclear explosions is highly dependent upon the actual yield of the explosion and its interaction with the environments in which the detonation occurs. These environmental factors can be characterized by the depth of explosion below the surface, the degree of coupling between the charge and the adjacent medium, and the lithological nature of the test sites. Therefore, the analysis of rock type at the test sites is the first step in nuclear monitoring.

The LANDSAT data have been determined effective for terrain analysis. The choice of the LANDSAT imagery for rock types analysis at the nuclear test sites is also based upon the fact that it can provide world-wide coverage with repetitive observations for monitoring purposes. The goal of this study is to test the feasibility of utilizing LANDSAT's digital, multi-spectral reformation for rock types discrimination at the nuclear test sites, based on the texture-tone analysis algorithms of the image processing systems at Susquehanna Resources and Environment, Inc.

The experiments were based on two subframes of LANDSAT MSS data, covering two geological quadrangles of Nevada. Whereas Site 1 (Antler Peak Quad) was used mainly for methodological development, Site 2 (Duffer Peak Quad) was designed as an analog test site to foreign areas for performing the task of extracting the granite regions.

The task was accomplished by using two separate but complimentary image processing techniques. The first technique, a supervised classification, was designed to extract granite regions using four ratio bands (4/7, 4/6, 5/7, and 6/7) based upon four manually selected, but automatically pre-processed training sets. The non-granite regions were extracted as well

using the reject category of the classification model. The second method, an unsupervised classification procedure based on the concepts of region growing and texture analysis, was designed to delineate granite regions using one ratio band (4/7 is most effective) by growing the granite regions from the cores of the training sets to the edges bordering non-granite areas.

The final granite regions were defined by the intersection of two granite images produced by two different image analysis techniques. The result indicates that a very high level of correct classification rate--95 percent or better--has been achieved, based on an overlay analysis using the classification result against the geologic map produced by the U.S. Geological Survey.

Though the defined task of extracting granite regions has been successfully accomplished, it is necessary to test the developed image processing and analysis techniques using additional U.S. test sites before they are applied to foreign regions. The reasons are (1) fine tuning of the methods are required to handle diverse patterns of lithological associations, and (2) the LANDSAT imagery can be exploited further for detecting environmental and man-made changes before and after nuclear explosions.

Applications of Texture Analysis for Rock Types Discrimination

Section A: Introduction

Ever since the Soviet Union's detonation of its first nuclear device prototypes, both the realities of an arms race and the requirement to maintain scientific/technological advantages have forced the United States to expend significant resources in monitoring of foreign nuclear tests. Sophisticated technologies that have evolved about the framework of seismology and geophysics have made significant contributions in satisfying the national requirement to detect, locate, identify and yield-quantify world-wide nuclear detonations. Yet, there is room for improvement using non-seismic methods, particularly in the area of yield estimation. To this end, this study is intended to develop image processing and analysis methodologies for the discrimination and identification of rock types at nuclear test sites. The rationale of this approach is based on the fact that the recorded seismic wave energy resulted from nuclear explosion depends on the following environmental/lithological factors:

(1) the actual yield of the explosion;

(2) depth of the explosion below the surface;

(3) the degree of physical coupling between the charge and the adjacent medium; and

(4) the geological nature of the median in which the detonation occurs.

Indeed, rock types analysis is the first step in yield estimation.

To accomplish the goal of rock types discriminated at the nuclear test sites, LANDSAT's multispectral data were used. The choice of the LANDSAT imagery is based on the fact that it is capable of providing a world-wide and repetitive coverages and thus a basis for monitoring nuclear test activities. The thrust of this study is to exploit the digital information of LANDSAT data in the context of texture-tone analysis for such purposes.

To test the feasibility of the SR&E's image processing system for lithological analysis, two test sites in Nevada were utilized, the Antler Peak Quadrangle, Nevada at the scale of 1:62,500 (ANA1) and the Duffer Peak Quadrangle, Nevada at 1:48,000 (ANA2) as analogs to foreign nuclear test sites. Specifically, the first site (ANA1) was used as a testbed for methodological development; whereas the second site (ANA2) was designed as an analog area for extracting granite regions.

To classify granite versus non-granite regions, two complementary image analysis techniques were employed. First, a supervised classification analysis was conducted to delineate granite areas based on manually selected, but digitally pre-processed training sets, and to reject non-granite regions based on a pre-set statistical model/probability level for identifying pixels which are significantly different from the training sets. Second, an unsupervised clustering analysis based on SR&E's Region Growing Texture Clustering algorithm was performed to extract granite areas by region growing from the cores of the granite training sets. The final definition of granite regions is based on the intersection of these two sets of "granite maps."

Section B: A Brief Review of Relevant Literature

Prior to 1972 and the launch of LANDSAT, pioneer work on reflective properties of minerals was accomplished by Hunt and Salisbury at the USAF Cambridge Research Laboratories (1970, 1973). Their study and explanation of reflective/transmission properties of both minerals and rocks in the visible and near-infrared regions serves as a basis for semi-automatic rock discrimination to techniques that exploit the spectral (tone) parameters of multispectral imagery. Rather than being a simple empirical result, it turns out that minerals and rocks spectral characteristics are a direct function of the physics and theory associated with crystal-field theory (Burns, 1970), as evidenced from theoretical and laboratory analyses of the rocks and minerals of the moon (McCord, 1968; further McCord, et al, 1972).

Since then, scientists at the U.S. Geological Survey, Jet Propulsion Laboratory and NASA/Goddard Space Flight Center, have attempted to exploit LANDSAT MSS data for rock types analysis as evidenced from Goetz, et al (1973), Goetz, et al (1975), Vincent, et al (1975), Rown, et al (1976), Rown, et al (1977), Abrams, et al (1977), and Podwysocki, et al (1977). Recent work by other researchers including Lyon (1977), Lyon, et al (1978), Hunt (1977), and Siegrist et al (1980), also emphasized digital processing of LANDSAT and other types of multispectral scanner data for optimal combination of spectral channels for rock discrimination.

While the majority of the work cited above emphasized rock types analysis and identification with color enhancement techniques with LANDSAT images, our study is devoted exclusively to extracting rock types using the digital information of the LANDSAT MSS data in the context of texture analysis, which has been largely neglected by previous researchers.

Section C: The Tasks, Data Analysis and Results

1. Tasks to be Accomplished

a. Preliminary Testing on the Proposed Methodologies

At the beginning of our research, the task was loosely defined as discrimination of rock types with LANDSAT data using our texture analysis algorithms.

Using more than 20 training sets evenly distributed over the entire Site 1 (Antler Peak Quad.), it was determined that (1) our texture algorithm is capable of separating these training sets with a correct classification rate of over 95 percent even though many of the training sets belong to the same major rock types--sedimentary, igneous and metamorphic; and (2) while the three major rock types are well separated, in terms of statistical means of texture-tone variables, the range of these measurements from training sets within the same major rock-type is not small for all training sets, meaning that local variations exist in major rock types.

In the mapping analysis, it was determined that our region-growing texture clustering algorithm is apparently effective in delineating surface material which may be relatable to the bedrock information with LANDSAT data without compression. It is not effective when the LANDSAT data are compressed by a factor of three.

b. Tasks Determined for the Phase-I Effort

From a discussion session among Mr. Best of AFOSR, Col. Lowrey of DARPA, Mr. Rachlin and his colleagues of U.S. Geological Survey, and Dr. Hsu, it was determined that the tasks of our effort should be aimed at answering the following three questions:

1. How well can we map the granite areas versus non-granite regions using our supervised and unsupervised classification methods in the context of texture analysis?

2. What are the factors affecting the classification results--slope, drainage pattern, data used, methodologies utilized?

3. What are the potential contribution of image processing techniques and methodologies towards the discrimination and even identification of rock types using LANDSAT data?

For data analysis, a study area within Duffer Peak Quadrangle, Nevada was selected by Mr. Dempsie of U.S. Geological Survey. Furthermore, based on the geologic map, 22 training sets were selected manually to cover four major rock types: (1) granite, (2) metamorphic, (3) volcanic, and (4) unconsolidated.

2. The Data Sets

a. The Original Data Set from the LANDSAT Tape

Corresponding to the study area selected by Mr. Dempsie of U.S.G.S., a digital set composed of (256 x 256) pixels of LANDSAT MSS data was determined using visual analysis. The Northwest corner of the data set is located at (row 1268, column 1987).

In addition, the training sets with their locations within the (256 x 256) frame have also been determined as follows:

1. Group 1: Granite

G1: (15,124), (15,144), (27,144), (27,124)

G2: (56, 38), (56, 55), (71, 55), (71,38)

G3: (130,133), (130,147), (142,147), (142,133)

G4: (132,7), (132,19), (146,19), (146,7)

G5: (170,137), (170,150), (181,150), (181,137)

2. Group 2: Metamorphic

B1: (75,158), (75,172), (85,172), (85,158)

B2: (115,163), (115,182), (129,182), (129,163)

B3: (150,175), (150,189), (166,189), (166,175)

B4: (95,89), (95,106), (105,106), (105,89)

3. Group 3: Volcanic

H1: (213,144), (213,159), (221,159), (221,144)

H2: (215,174), (215,190), (223,190), (223,174)

H3: (241,186), (241,197), (248,197), (248,186)

H4: (217,13), (217,25), (228,25), (228,13)

F1: (188,81), (188,93); (197,93), (197,81)

F2: (228,106), (228,117), (235,117), (235,106)

F3: (213,124), (213,134), (222,134), (222,124)

T1: (234,68), (234,80), (243,80), (243,68)

T2: (246,100), (246,112), (254,112), (254,100)

4. Group 4: Unconsolidated

Q_o1: (132,51), (132,64), (139,64), (139,51)

Q_f1: (51,196), (51,207), (61,207), (61,196)

Q_f2: (150,212), (150,223), (158,223), (158,212)

Q1: (56,237), (56,249), (65,249), (65,237)

b. Derived Data Sets to be Analyzed

To remove the shadow effect of the original LANDSAT data, and to extract information from four MSS bands simultaneously, the following date sets are generated.

(1) First, second and third components from the four MSS bands;

(2) Six ratio bands from the four MSS bands: 4/5, 5/6, 6/7, 4/6, 4/7, and 5/7.

(3) The first component map from 4 selected ratio bands.

Therefore, ten derived image data sets are available for analysis in addition to the original four MSS bands. The location of the training sets with respect to these derived data sets remain the same.

3. Image Processing and Data Analysis Methodologies Utilized

To analyze the relationship between the selected training sets, and to classify the granite areas versus non-granite regions, the following analytical techniques are utilized.

a. Extraction of texture-tone information of the training sets and the entire data set.

Using the texture-tone extraction algorithm, 23 texture-tone-ratio variables have been generated for any given pixel from four multi-spectral bands using (3 x 3) moving grid. They are composed of 4 tone variables, 12 texture variables (3 from each band), 1 linear feature variable, and final 6 ratio variables.

For data analysis, the analyst is able to select a portion of the 23 variables.

b. Analysis of the Training Sets

Based upon the selected variables from 23-variable system, typically we use three variables, the training sets will be analyzed and edited so that each training set will meet the following two criteria:

(1) single mode; if two modes exist in one training set, the set will be split into subsets;

(2) extreme outliers are to be removed based on a statistical confidence level.

c. Discriminant Analysis of the Training Sets

After the training sets are edited or preprocessed, they will be analyzed in terms of how close they are between pairs of training sets using the means of selected tone-texture variables. The distance is generally measured by statistical distance called Mahalanobis D^2 with or without a log-determinant term.

While the D^2 distance is indicative of the degree of similarity and dissimilarity between two training sets, the analyst usually uses a confusion matrix--classification result using only the training sets--to examine how well these training sets are separated. The analyst will then decide whether he should proceed with a classification analysis of the entire test set. In general, if dissimilar training sets are confused, a classification analysis should not be conducted.

d. Supervised Classification Methods

As mentioned earlier, a supervised classification analysis can be made only when the training sets are well separated. To achieve this goal, the following steps can be taken:

(1) purify the training sets as in (b);

(2) change the location of the training sets;

(3) increase the power of the feature extractor by using (i) more texture-tone variables, and (ii) using different spectral-band combinations; and

(4) increase the power of the classifier by using a non-Gauseian model if the data are essentially non-multivariate normal.

In the analysis, we have done all thse image processing techniques except step (2), changing the location of the training sets.

e. Scene Segmentation with Unsupervised Training/Classification Method

This analysis is intended to extract the granite regions first based on segmentation concept using a region-growing texture clustering algorithm. Once the entire test area is segmented into numerous subregions according to different levels of thresholding (generalization), we are able to extract the granite regions according to the location of the training sets.

Since this algorithm is based on local statistics or edge information instead of global separation employed by the supervised classification method, it should be used as a complementary classification method instead of a replacement of the supervised method.

f. Comparative Analysis with the Results from Supervised and Unsupervised Classification Method

g. Analysis of Factors Influencing the Classification Results

In this analysis we will concentrate our effort on two broad categories: (1) classification results influenced by terrain factors, surfacial material, slope, drainage, etc., and (2) classification results influenced by the data sets and techniques, feature extractors, and classifiers, used in the analysis.

4. Experiments Conducted and Research Results

The description of this section regarding data analysis corresponds to the methodologies discussed in the previous section.

a. Generation of Texture-tone Variables for Data Analysis by Supervised Classification Methods

Using the original LANDSAT MSS data and dervied ratio bands, these data sets containing 23 texture-tone variables for each pixels were generated:

(1) Data Set 1 is composed of MSS Bands 4, 5, 6, and 7;

(2) Data Set 2 is composed of 4 ratio bands: 4/5, 5/6, 6/7 and 4/7; and

(3) Data Set 3 is composed of 4 ratio bands: 4/7, 4/6, 5/7 and 6/7.

b. Analyses of the Training Sets

The training sets selected manually by Mr. Dempsie of U.S. Geological Survey were analyzed for two distinctive purposes:

(1) All 22 training sets were analyzed to detect the confusion pattern between the granite sets and the non-granite sets; and

(2) Four granite sets of the original five granite sets were preprocessed for serving as calibration samples for classification analysis.

The anlaysis starts with preprocessing of the training sets aimed at detecting whether bi-modal distribution and outliers exists in each set.

Indeed, it was determined that in the original MSS data sets B2, B3, B4, T1 and Q_o1 are bi-modal, and thus each was split into two subsets, resulting in 28 training sets, instead of 22 sets in original design. Furthermore, outliers are edited and eliminated using a predetermined distribution scheme. Table 1 summarizes the training sets information, original and after preprocessing, whereas Appendix 1 gives the sample statistics of the texture-tone variables for each training set.

Using the statistics given in Appendix 1, an analysis was conducted to reveal the confusion pattern between the granite training sets (set 1 through set 5) and the rest. The results are given in Table 2, and it indicates that (1) granite set 1 is highly confused with non-granite sets, and (2) granite set 2 through set 5 are highly correlated among themselves, but are not confused with non-granite sets (set 6 through set 28). For instance, the percentage of correct classification of G1 into G1 through G5 is only 61.7, whereas the figures for G2, G3, G4 and G5 are 100, 86.1, 99.5 and 99.4, respectively. It was therefore determined that training set G1 should be eliminated from the design sets in the final classification analysis aimed at delineating granite versus non-granite regions.

The same analyses were also applied to the training sets with ratio data, instead of the original MSS data. Whereas Appendix 2 gives the texture-tone statistics of each training set, Table 3 summarizes the result of preprocessing; from the original 22 sets, 25 sets are obtained, instead of 28 as in the case of the original MSS data. This means that the ratio data are more homogeneous than the raw MSS data because the LANDSAT's shadow effect has been removed by the ratioing process.

In terms of confusion pattern between granite sets versus non-granite sets, no significant difference exists between the raw MSS data and the ratio data, as indicated in Table 4; namely, granite set 1 is totally confused with other non-granite sets, granite set 2 through granite set 5 are similar among themselves, but quite different from other non-granite rocks.

Raw Data

Table 1: Preprocessing of the Training Sets with Original MSS Data (Band 4 and Band 7)

Original Training at ID #		Code	Training Set Size (1) # of Points	Training Set Size (2) after Preprocessing	New Set ID New Training Set ID #
1	Granite	G1	273	269	1
2		G2	288	278	2
3		G3	195	190	3
4		G4	195	187	4
5		G5	168	164	5
6	Metamorphic	B1	165	162	6
7		B2	300	141 154	7 8
8		B3	165	95 70	9 10
9		B4	198	91 92	11 12
10	Volcanic	H1	144	143	13
11		H2	153	150	14
12		H3	96	96	15
13		H4	156	93 63	16 17
14		F1	130	126	18
15		F2	96	94	19
16		F3	110	108	20
17		T1	130	64 51	21 22
18		T2	117	111	23
	Unconsolidated				
19		Q_f1	132	131	24
20		Q_f2	108	105	25
21		Q1	130	130	26
22		Q_o1	112	58 50	27 28

Table 2: Confusion Matrix: Percent of Correct Classification

With the Raw Data

New ID #	1	2	3	4	5	6	7	8	9	10	11	12	13	14
G1	6.06	0	1.1	0	0	7.1	0.7	3.8	0	2.6	0	0.4	1.1	8.2
G2	0	82.4	0	17.3	0.4	0	0	0	0	0	0	0	0	0
G3	0	0	84.7	0.5	9.0	0	0	0	0	0	0	1.6	0	0.5
G4	0	18.2	0.5	75.4	3.7	0	0	0	0	0	0	0	0	0
G5	0	4.9	6.7	0	81.1	0	0	0	0	0	0	0	0	0.6

New ID #	15	16	17	18	19	20	21	22	23	24	25	26	27	28
G1	1.9	3.4	0	0.4	1.5	0.4	0	0.4	2.2	0	2.2	2.2	0	0
G2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G3	1.1	0.5	0	1.1	0	0.5	0	0	0	0	0	0	0	0.5
G4	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5
G5	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 3: Preprocessing of Training Sets with Ratio Data

Training Set ID #		Code	# of Points	After pre-processing	New ID #
1	Granite	G1	273	258	1
2		G2	288	278	2
3		G3	195	186	3
4		G4	195	178	4
5		G5	168	162	5
6	Metamorphic	B1	165	165	6
7		B2	300	183 111	7 8
8		B3	165	74 83	9 10
9		B4	198	196	11
10	Volcanic	H1	144	143	12
11		H2	153	150	13
12		H3	96	93	14
13		H4	156	154	15
14		F1	130	127	16
15		F2	96	93	17
16		F3	110	108	18
17		T1	130	127	19
18		T2	117	115	20
19	Unconsolidated	Q_f1	132	130	21
20		Q_f2	108	105	22
21		Q1	130	63 57	23 24
22		Q_o1	112	111	25

Table 4: Confusion Matrix Between Granite and Non-Granite Sets with Ratio Data (B4/B7, B4/B6, B5/B7, B6/B7)

	1	2	3	4	5	6	7	8	9	10	11	12
G1	13.2	0	0	0	1.2	0.4	2.7	1.9	1.6	0.4	13.2	1.2
G2	0	48.2	0	13.7	25.5	0	0	0	0	0	0.4	0
G3	0	0	32.8	0	61.3	0	0	0	0	0	1.6	0
G4	0	7.3	0.6	37.1	31.5	0	0	0	0	0	0	0
G5	0	0	0.6	0	99.4	0	0	0	0	0	0	0

	13	14	15	16	17	18	19	20	21	22	23	24	25
G1	3.5	3.5	0.4	6.2	7.0	5.4	8.1	27.9	0	1.6	0.4	0.4	0
G2	0	0	0	0	0	0	0	0	2.5	0	0	0	9.7
G3	9.5	2.7	0.5	0	0	0.5	0	0	0	0	0	0	0
G4	0	0	0	0	0	0	0	0	0.6	0	0	0	23.0
G5	0	0	0	0	0	0	0	0	0	0	0	0	0

In terms of the confusion pattern among these 4 granite sets, it was determined that they are related only to a certain degree since tbe correct classification rate with the form sets reach at a high level of 75 percent (Table 5). This means significant local variation of granite exists in the study area.

Table 5. Confusion Matrix of the Granite Training Sets

	G2	G3	G4	G4
G2	211	0	63	5
G3	0	164	2	20
G4	62	2	113	2
G5	12	31	19	102

Correct Classifier = 73.02%

c. <u>Classification Analyses with a Supervised Training Approach</u>

The goals of this anlayses are first to generate classification maps of granite versus non-granite regions using different data sets, different feature variables and different classifiers, and second to compare these classification results against the ground truth information including terrain information and bedrock geologic map.

For the study, numerous experiments have been conducted; the following table indicates the experiments derived from combinations of different data sets with different methodologies.

Table 6. Experiments of Supervised Classification

Data Sets / Methodology	Data Set 1 (4 original MSS)	Data Set 2 (4 ratio bands: 4/5,4/5,5/7,4/7)	Data Set 3 (4 ratio bands: 4/7,4/6,5/7,6/7)
1. Gaussian Classifier with 7 texture-tone variables	Exp 1 with 5 granite sets Exp 2 with 5 granite sets plus 5 automatically selected new sets	Exp 1 with 4 granite sets Exp 2 with 4 granits sets plus 2 automatically selected new sets	Exp 1 with 4 granite sets
2. Gaussian Classifier with 16 texture variables		Exp 1 with 4 granite sets	
3. Non-Gaussian classifiers with 7 texture-tone variables		Exp 1 with 4 granite sets	Exp 1 with 4 granites sets

From these experiments, it can be concluded that:

(1) For rock type analysis, Data Set 3 composed of these 4 ratio bands: 4/6, 4/7, 5/7, 6/7 is most effective. Data Set 1 with the 4 original 4 LANDSAT MSS bands is least affective. Figure 1, a decision map, indicates that the vast majority of granite areas are correctly identified, except

(a) the granite area, within which the training set G1 (which was not used in the analysis is located, is largely classified as non-granite, and

(b) one "metamorphic rock" area as labeled in the geologic map was largely classified as "granite."

These two regions will be investigated further using our unsupervised segmentation algorithm in the next section.

(2) Regarding the classifiers, our Non-Gauusian classifier with 7 texture-tone variables is superior to the Gaussian classifier no matter whether it utilizes 7 or 16 texture-tone variables.

(3) There is little difference between 7-variable Guassian classifier and 16-variable Gaussian classifier in terms of the confusion matrix using the training sets data.

(4) In terms of correct classification of the granite versus non-granite regions (areal distribution), both our Gaussian and non-Gaussian classifiers achieved a level of over 90 percent hit-rate. The Non-Gaussian Classifier is slightly better than the Gaussian Classifier in these experiments.

d. Feature Extraction with an Unsupervised Training Approach

(1) Experimental Design

The goal of these analyses is to extract homogeneous regions in the study area from various LANDSAT ratio bands using our region-growing texture clustering analysis algorithm. Identification of the granite regions becomes a labeling process using training sets information and other related statistical and terrain characteristics data. It is our intention to use the results from this unsupervised classification method to investigate the areas of misclassification by the supervised classifier.

From the four LANDSAT MSS bands, it is possible to derive six ratio bands: 4/5, 4/6, 4/7, 5/6, 4/7, and 6/7. In our earlier experiments, it was determined that these ratio bands are not effective for segmenting regions of the study area: 4/5, 5/6 and 6/7. Hence, our experiments for rock-type/surface material analyses utilized information from these three ratio bands: 4/7, 5/7, and 4/6. These three ratio bands in fact characterize the contrast between the visible and the infrared spectrum.

To extract rock-type/surface material regions, the following experiments were conducted using our unsupervised classification

("Region") algorithm:

Experiment	Data Set	Thresholding Parameter	No. of Passes
1	A2R47F3	(2,2) through (2,5)	5
2	A2R47F3	(3,3) through (3,6)	4
3	A2R47F3L	(2,2) through (2.6)	5
4	A2R57F3	(3,3) through (3,7)	5
5	A2R57F3L	(2,2) through (2,5)	4
6	A2R46F3	(2,2) through (2,7)	7
7	A2R46F3L	(2,2) through (2,4)	3

For the data set ID, A2 means Analog Area 2 of the study areas; R47 means ratio between Band 4 and Band 7; and F3 means the third data file (Analog 2) and L in the data set name identifies the fact that the data set is derived from double log ratio mode.

Regarding the thresholding parameters, the first parameter stands for the first stage cutoff regarding the difference between adjacent (pairs) pixels or clusters; whereas the second parameter refers to the second stage cutoff for grouping clusters in terms of a weighted geometric distance computed from a tone and a texture variable.

Since we design the algorithm to perform a dynamic cueing task, the analytical results can be printed (output) at any given stage of clustering process according to the second stage cut-off parameter specified by the analyst. Furthermore, the statistics for each region of a given pass can be extracted and displayed.

(2) <u>The Results of the Analyses</u>

By examining the results from these experiments, it can be concluded that:

(a) General conclusions:

(i) In general, the "Region" algorithm is able to extract spatially contiguous, homogeneous regions of rock-type/surface material regions as defined by the contrast between visible and infrared spectrum of the LANDSAT data;

(ii) The performance of a given ratio band is not uniform over the entire study area, meaning that it may take two or more ratio bands to extract all of the "distinctive" regions in the study area.

(iii) Our "dynamic cueing" approach is able to reveal the strength and weakness of the contract lines or zones between two adjacent rock-type/surface-material regions. This means that the existence of "contact lines or zones" is both spectral/spatial information dependence, and thresholding parameter dependence as well.

(iv) In the area where the supervised training classifier failed to identify the granite and non-granite regions, the unsupervised, region-growing algorithm is capable of identifying them as distinctive regions.

(v) Combining the results from the supervised and the unsupervised classification approaches, we believe that the correct classification rate of granite versus non-granite region is about 95 percent.

(vi) Therefore, it can be concluded that our two classification algorithms are indeed complementary for extracting distinctive rock-type/surface-material regions.

(b) Conclusions from individual experiments:

(i) Results from Log Ratio of Band 4 and B7 (Figure 2). The base map of Figure 2 is the Pass 3 results of the unsupervised classification with log ratio of Band 4 and Band 7. Using the location of the training sets G1 through G5, the major granite areas are identified and colored in light red, whereas the bedrock regions of granite are shaded in green. In general, there is a high degree of agreement between the segmented regions and the bedrock boundaries. Particularly, by comparing Figure 2 against Figure 1, we are able to derive that (1) the rejected granite G1 area can be delineated by the Region algorithm, and (2) the confused area in Figure 1 between G2 and G3 can be discriminated as well. Similar to the supervised classifier, the Region algorithm failed to distinguish the bedrock granite from the surfacial granite in the area near training set G4. As will be noted later, this boundary is detected in the analysis with the data set of log ratio of Band 4/Band 6.

(ii) Results from Log Ratio of Band 4 and Band 7 with a Larger First Stage Cutoff. This experiment was intended to reveal the effect of using a larger first stage cutoff parameter as compared to the above experiment. The results indicate that with a larger cutoff the algorithm failed to detect the boundary between granite versus non-granite in the area where training set G1 is located; the rest of the results remains essentially the same.

(iii) Results from Double Log Ratio of Band 4 and Band 7 (Figure 4). This experiment shows the effect of using a double log transformation of the data set Band 4/Band 7. By comparing the result against Figure 2, it can be noted that this double transformation in fact has less discrimination power as evidenced from the fact that there is boundary shift in the area near training sets G2 and G5.

(iv) Results from Log Ratio of Band 4 and Band 6. In this experiment, we replaced Band 7 with Band 6 of the LANDSAT infrared spectra and kept Band 4 as a constant. The result shows that (1) log ratio of Band 4 and Band 6 is able to detect the boundary between bedrock granite and surfacial granite as evidenced from the area near the location of G4, but (2) it failed to detect the granite versus non-granite boundaries in the areas where G1 and G4 are located. In general, it appears that the spectral data from ratio of Band 4/Band 6 contain a component which is affected by the drainage pattern of the area.

(v) Results from Log Ratio of Band 5 and Band 7. This experiment shows the effect regarding a change in the visible band in the analysis, and the results indicate that the ratio of Band 5 and Band 7 is less effective for rock type analysis as compared to B4/B7. It appears that the B5/B7 data set contains a component which is highly affected by the drainage patterns of the area.

(vi) Results from Double Log Ratio of Band 5 and 7. In general this experiment indicates that in certain regions the double log transformation of ratio data of B5/B7 may be more sensitive than the single log transformation as evidenced from the segmentation results in the area where training set G1 is located.

e. Classification Analysis by a Combination of Supervised and Unsupervised Training Approaches

From the results given in Sections c and d, we have used a multiple map overlay analysis to delineate the final granite regions as given in Figure 3 with the following conclusions:

(1) In the areas where training sets information exists, there is a remarkable correspondence between Figure 1 and Figure 2;

(2) From a manual editing process, we can place the granite G1 area from Figure 2 onto Figure 1;

(3) The areas of misclassification in Figure 1--

i. region between G2 and G3, and

ii. pixels located outside the boundaries of labeled granite regions of G1, G2, G3, G4 and G5 in the northeast, southeast and southwest quadrangles--

can be removed from Figure 1.

(4) Since there is no information regarding ground truth in the area between the location of G1 and G2, we will use the result as given in Figure 1 for granite identification; and

(5) Comparing the results as described above in reference to Figure 3, it can be concluded that an extremely high level of correct classification of granite and non-granite has been achieved. It should be noted that we are able to edit this map further using additional ground truth information and the segmentation results given by other ratio bands.

Section D: Image Processing Techniques Towards Identification of Rock Types

1. Integration of Supervised and Unsupervised Classification Methods.

As indicated in Section C, the task of identifying rock types can be achieved provided that ground truth information of the training areas is known. The task can be achieved by using either a supervised or unsupervised classification technique as shown in Figure 1 and Figure 2, respectively.

To obtain a better result, the intersection of these two classification maps (Figure 3) was used as the final decision rule for defining the granite regions. The advantages of Figure 3 over Figure 1 and Figure 2 are several:

(1) It avoids random errors in the decision map of the supervised classification methods, particularly those located far away from cores of the training sets;

(2) It has information for labeling segmented regions from the unsupervised classification method; and

(3) the intersection of two decision maps in fact, strengthens the probability of correct classification.

In this report, the "intersection" of two classification methods was done by use of an overlay analysis of two decision maps.

Theoretically, a new algorithm should be developed to perform the task of merging two image processing methods centered around:

(1) Classifying the results of the region algorithm using the training sets information, and

(2) Extracting distinctive regions using multiple ratio bands, and classifying them according to the training sets information.

It is believed that certain techniques of artificial intelligence are useful to this effort.

2. Fine-tuning of the Region Algorithm.

a. Dynamic edge patterns as indication of rock types

For this technical report, the region algorithm was utilized to segment terrain/rock types in multiple stages, and to reveal the evolutional patterns of the edges, such as lineaments or contact zones between two lithological types, at the study area.

An improvement of the region algorithm can be made by adding a subroutine aimed at testing whether edges within a larger region are noise or real boundaries. If they are determined as noise, they can be removed, and vice versa. This capability will provide the anlayst with a sounder basis for the regionalization of terrain and lithological types.

b. Display Texture and Tone Information of each Segmented Region

To provide more information for the analyst to make decisions regarding identification of rock types, another subroutine can be added to output the texture, tone and size information of the segmented regions under investigation. Using such information, the analyst may be able to identify the terrain and rock types by means of a comparative analysis provided that certain texture-tone characteristics of training areas are known.

In practice, the analyst would use both edge pattern and quantitative texture-tone information for rock types discrimination and identification.

c. Generalization by a Color Prediction Model

Conventionally color monitors are used as a device for generating color composite from multi-channel data by means of a coding process using three color primaries, red-green-blue or yellow-cyan-magenta.

With known quantitative texture and tone information, specific colors can be generated for a given rock type by means of the color theory. For instance, if there are two parameters (1 tone and 1 texture) for each region, a specific color for that region can be made by assigning the tone information to Red domain and the texture information to Blue versus Green domain. If three parameters are available, 1 tone and 2 textures, the specific color code for that region can be generated by assigning tone to Red, texture 1 to Green, and texture 2 to Blue.

For the two-parameter system, different color/tensity codes can be generated if one allows the tone parameter to control intensity levels and texture to control colors. In an 8-bit color monitor system, for instance, one can allow the tone parameter to display 16 intensity levels, and the texture variable to give 16 different colors. The combination of such intensity and color codes should allow the researcher to predict and identify certain rock types using given texture and tone information from either ground truth or laboratory analysis, or a combination of both.

Figure 1

Classification Map of Granite Regions, Supervised Method, Non-Gaussian, Ratio Bands: 4/6, 4/7, 5/7, 6/7.

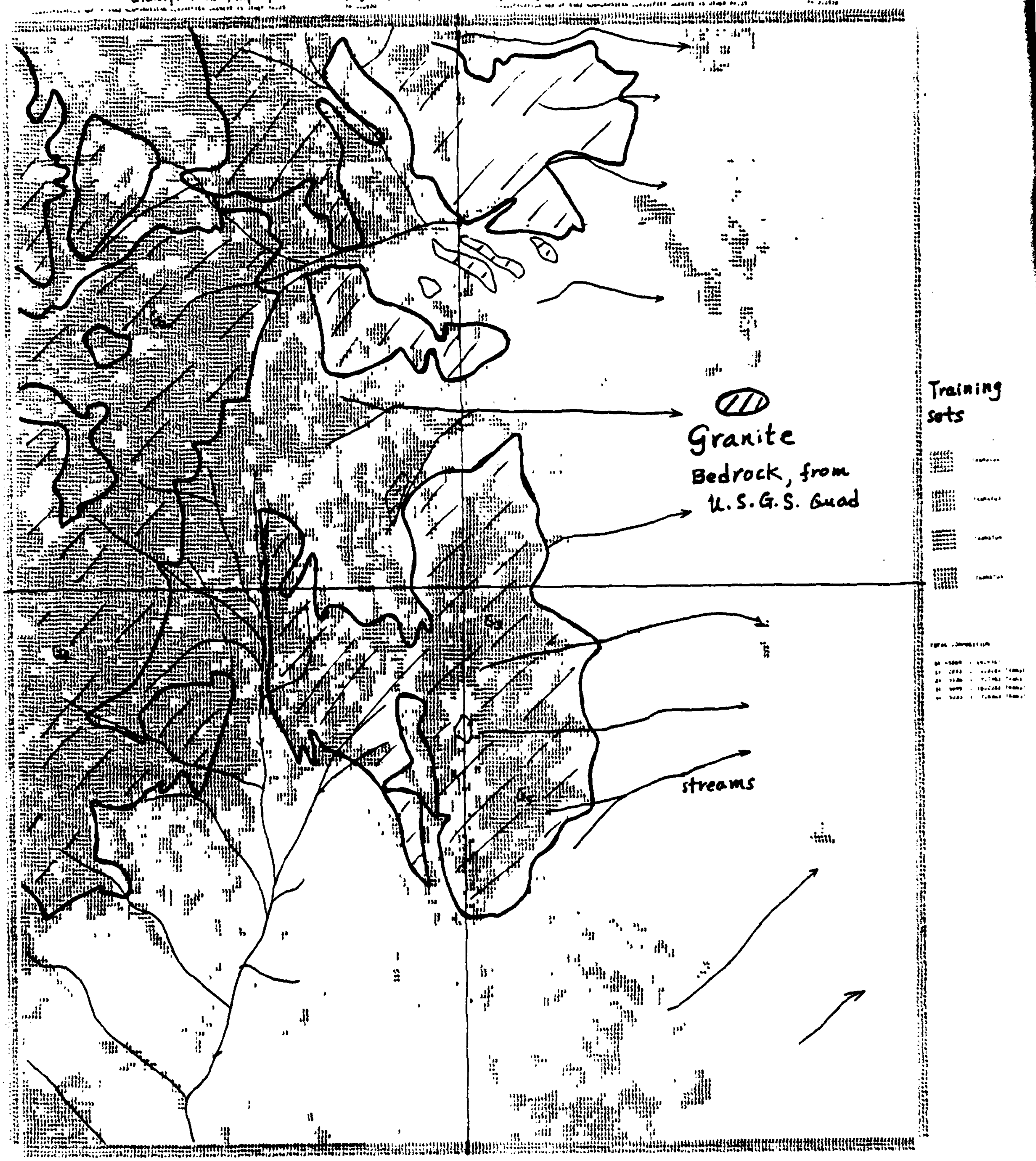


Figure 2:

Dynamic Regions of Granite by Unsupervised Classification Method
Based on Logratio of Band 4 / Band 7

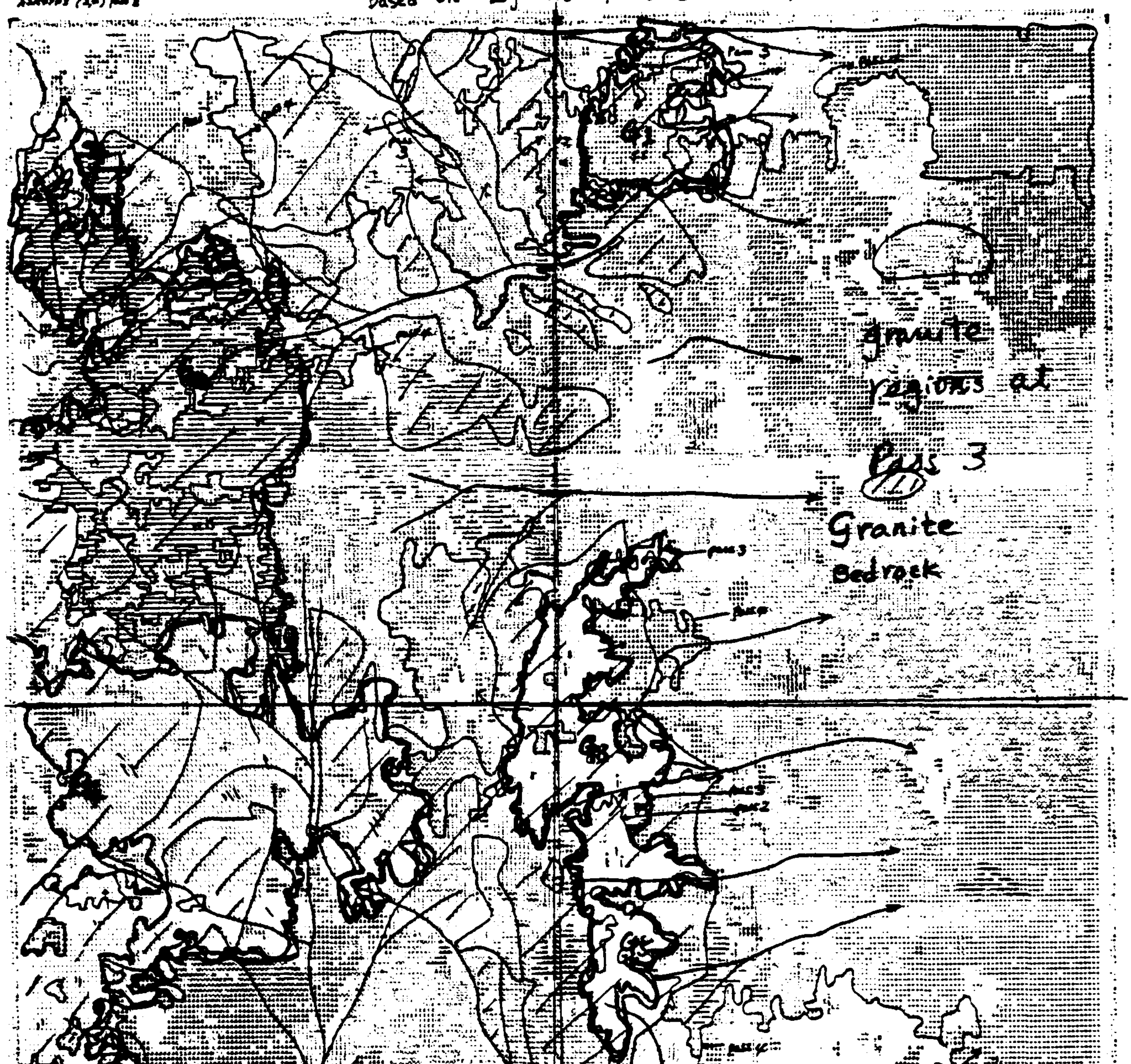
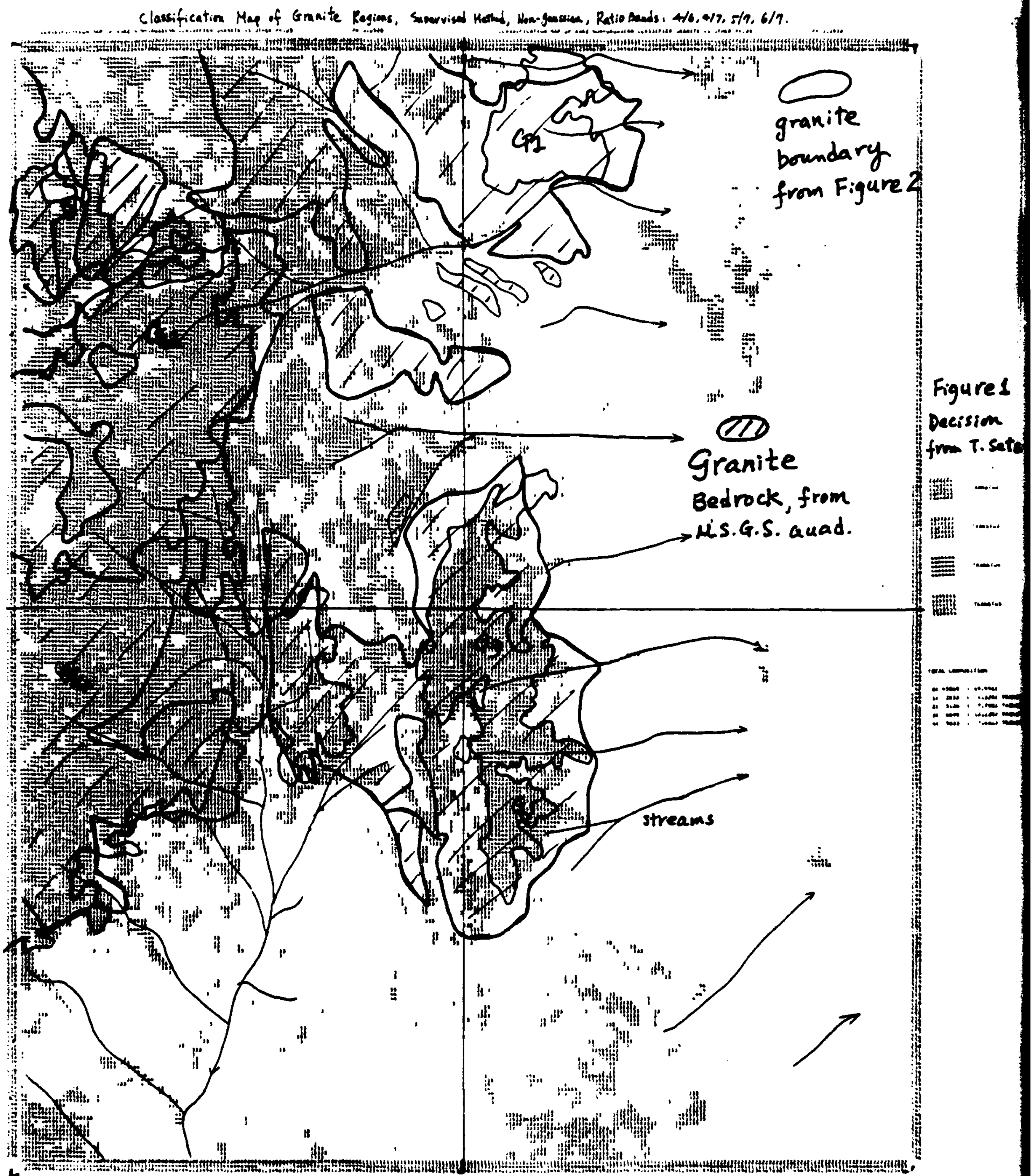


Figure 3: Decision map from Overlay of Figure 1 and Figure 2



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APPENDIX 1

Texture and Tone Variables of the Training Sets with the Original LANDSAT MSS Data

DISCRIMINANT ANALYSIS   SIMPLE STATISTICS

SET = 1

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	269	7275.44600000	27.04626766	10.61336356	3.25781577
BRIGHT5	269	9716.44100000	36.12059851	25.12891821	5.01287524
BRIGHT6	269	10653.99500000	39.60592937	29.51138077	5.43243783
BRIGHT7	269	8611.66700000	32.01363197	22.23781780	4.71569908
MINCON4	269	478.34100000	1.77821933	0.45377954	0.67363161
MINCON5	269	713.41900000	2.65211524	0.87622930	0.93607120
MINCON6	269	868.59300000	3.22897026	1.15564759	1.07501051
MINCON7	269	794.74400000	2.95443866	0.88961799	0.94319562
MDEVN4	269	462.11600000	1.71790335	0.53609425	0.73218457
MDEVN5	269	684.02200000	2.54283271	1.18679589	1.08940162
MDEVN6	269	848.98700000	3.15608550	1.59547732	1.26312205
MDEVN7	269	778.63600000	2.89455762	1.28419808	1.13322464

SET = 2

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	278	6884.66800000	24.76499281	24.62505162	4.96236351
BRIGHT5	278	9550.32700000	34.35369424	67.18083864	8.19639181
BRIGHT6	278	12416.22500000	44.66267986	61.27411160	7.82777820
BRIGHT7	278	11812.55200000	42.49119424	43.69071265	6.60989506
MINCON4	278	709.58100000	2.55244964	1.01921470	1.00956164
MINCON5	278	1099.32800000	3.95441727	2.09065145	1.44590852
MINCON6	278	1162.82900000	4.18283813	2.29213092	1.51397851
MINCON7	278	969.07700000	3.48588849	2.03917367	1.42799638
MDEVN4	278	671.82700000	2.41664388	1.11215723	1.05458865
MDEVN5	278	1049.18700000	3.77405396	2.61295830	1.61646475
MDEVN6	278	1076.09900000	3.87085971	2.76384021	1.66248014
MDEVN7	278	903.25700000	3.24912590	2.40167631	1.54973427

SET = 3

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	190	5390.77700000	28.37251053	20.18164973	4.49239911
BRIGHT5	190	7647.77700000	40.25145789	52.72212862	7.26100052
BRIGHT6	190	8691.66800000	45.74562105	57.61061605	7.59016575
BRIGHT7	190	7609.99900000	40.05262632	45.64013562	6.75574834
MINCON4	190	275.83700000	1.45177368	0.66831013	0.81750238
MINCON5	190	450.32900000	2.37015263	1.26206935	1.12341860
MINCON6	190	522.75100000	2.75132105	1.34906622	1.16149310
MINCON7	190	439.49900000	2.31315263	1.11173910	1.05439039
MDEVN4	190	282.07900000	1.48462632	0.79813033	0.89338140
MDEVN5	190	448.65900000	2.36136316	1.64334970	1.28193202
MDEVN6	190	513.43100000	2.70226842	1.81731243	1.34807731
MDEVN7	190	453.64800000	2.38762105	1.63351204	1.27808921

SET = 4

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	187	4712.66400000	25.20141176	29.79649193	5.45861630
BRIGHT5	187	6446.55200000	34.47354011	72.93618136	8.54026823
BRIGHT6	187	8256.55500000	44.15270053	68.15957279	8.25588110
BRIGHT7	187	7795.22000000	41.68566845	53.99631304	7.34821836
MINCON4	187	476.58500000	2.54858289	1.01019996	1.00508704
MINCON5	187	688.08600000	3.67960428	2.62444230	1.62001306
MINCON6	187	759.83500000	4.06328877	3.07809731	1.75445072
MINCON7	187	760.49800000	4.06683422	3.39574700	1.84275527
MDEVN4	187	445.65500000	2.38318182	1.16660871	1.08009662
MDEVN5	187	655.06100000	3.50300000	2.99072023	1.72936989
MDEVN6	187	711.68000000	3.80577540	3.37568778	1.83730449
MDEVN7	187	710.83400000	3.80125134	3.52116428	1.87647656

DISCRIMINANT ANALYSIS   SIMPLE STATISTICS

SET = 5

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	164	4469.55200000	27.25336585	5.10776661	2.26003686
BRIGHT5	164	6232.55800000	38.00340244	14.19187254	3.76721018
BRIGHT6	164	7424.00100000	45.26829878	9.28829390	3.04767024
BRIGHT7	164	6559.21500000	39.99521341	6.56286395	2.56180873
MINCON4	164	232.66200000	1.41867073	0.29115896	0.53959147
MINCON5	164	349.41700000	2.13059146	0.66595515	0.81606075
MINCON6	164	357.42200000	2.17940244	0.48427724	0.69590031
MINCON7	164	307.41600000	1.87448780	0.49954821	0.70678725
MDEVN4	164	217.45100000	1.32592073	0.25172126	0.50171831
MDEVN5	164	326.24500000	1.98929878	0.67358810	0.82072413
MDEVN6	164	324.04300000	1.97587195	0.58334838	0.76377247
MDEVN7	164	290.17000000	1.76932927	0.57967684	0.76136511

SET = 6

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	162	4638.99900000	28.63579630	2.46844277	1.57112787
BRIGHT5	162	6367.00200000	39.30248148	6.02707590	2.45501037
BRIGHT6	162	6720.00300000	41.48150000	10.55935075	3.24951546
BRIGHT7	162	5151.22300000	31.79767284	11.64255787	3.41211926
MINCON4	162	238.99700000	1.47529012	0.35425906	0.59519666
MINCON5	162	383.16600000	2.36522222	0.54831399	0.74048227
MINCON6	162	451.42000000	2.78654321	0.69143657	0.83152665
MINCON7	162	421.32800000	2.60079012	0.94665894	0.97296400
MDEVN4	162	223.08700000	1.37708025	0.33461366	0.57845801
MDEVN5	162	342.26700000	2.11275926	0.66120043	0.81314232
MDEVN6	162	410.62300000	2.53470988	0.86707270	0.93116739
MDEVN7	162	381.65100000	2.35587037	0.89797816	0.94761710

SET = 7

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	141	3810.77500000	27.02677305	4.14628981	2.03624404
BRIGHT5	141	5377.22100000	38.13631915	10.37580806	3.22115011
BRIGHT6	141	5681.77500000	40.29627660	10.76542219	3.28107028
BRIGHT7	141	4407.10400000	31.25605674	5.69515541	2.38645247
MINCON4	141	248.00000000	1.75886525	0.46478442	0.68175099
MINCON5	141	383.66100000	2.72100000	1.06235783	1.03070744
MINCON6	141	453.25200000	3.21455319	0.97781716	0.98884638
MINCON7	141	360.92100000	2.55972340	0.72224779	0.84985163
MDEVN4	141	220.02800000	1.56048227	0.40050505	0.63285468
MDEVN5	141	351.88000000	2.49560284	1.09611126	1.04695332
MDEVN6	141	411.13700000	2.91586525	1.00598393	1.00298750
MDEVN7	141	326.22000000	2.31361702	0.76483080	0.87454605

SET = 8

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	154	3378.44000000	21.93792208	11.26855696	3.35686713
BRIGHT5	154	4599.99800000	29.87011688	28.85196089	5.37140213
BRIGHT6	154	4929.99900000	32.01298052	32.12074537	5.66751668
BRIGHT7	154	3856.89500000	25.04477273	21.28090403	4.61312302
MINCON4	154	370.41000000	2.40525974	0.84367740	0.91851913
MINCON5	154	581.08700000	3.77329221	2.45577499	1.56709125
MINCON6	154	625.08500000	4.05899351	2.61054394	1.61571778
MINCON7	154	551.25200000	3.57955844	2.05133505	1.43224825
MDEVN4	154	365.55200000	2.37371429	0.85743032	0.92597534
MDEVN5	154	571.33600000	3.70997403	2.89316945	1.70093194
MDEVN6	154	604.34400000	3.92431169	2.81826139	1.67876782
MDEVN7	154	528.69400000	3.43307792	2.12433994	1.45751156

DISCRIMINANT ANALYSIS   SIMPLE STATISTICS

SET = 9

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	95	2447.77400000	25.76604211	1.46768568	1.21148078
BRIGHT5	95	3168.22500000	33.34973684	4.12392383	2.03074465
BRIGHT6	95	3211.10800000	33.80113684	3.28584895	1.81269108
BRIGHT7	95	2409.22400000	25.36025263	3.48917211	1.86793258
MINCON4	95	132.24900000	1.39209474	0.20312924	0.45069861
MINCON5	95	196.16900000	2.06493684	0.48639444	0.69741985
MINCON6	95	173.00200000	1.82107368	0.45968388	0.67799991
MINCON7	95	174.75100000	1.83948421	0.40720534	0.63812643
MDEVN4	95	111.70100000	1.17580000	0.11114574	0.33338527
MDEVN5	95	171.33400000	1.80351579	0.50060515	0.70753455
MDEVN6	95	154.07500000	1.62184211	0.38167073	0.61779506
MDEVN7	95	158.41700000	1.66754737	0.33673900	0.58029216

SET = 10

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	70	1523.44500000	21.76350000	5.89092156	2.42712207
BRIGHT5	70	1924.33700000	27.49052857	12.80131130	3.57789202
BRIGHT6	70	2054.33400000	29.34762857	12.81891676	3.58035149
BRIGHT7	70	1550.77600000	22.15394286	10.52061666	3.24355001
MINCON4	70	175.74900000	2.51070000	0.39977604	0.63227845
MINCON5	70	240.33100000	3.43330000	1.19326288	1.09236573
MINCON6	70	275.16800000	3.93097143	1.34786414	1.16097551
MINCON7	70	233.08000000	3.32971429	1.87502221	1.36931450
MDEVN4	70	169.00900000	2.41441429	0.55204990	0.74300060
MDEVN5	70	236.42000000	3.37742857	1.33128152	1.15381174
MDEVN6	70	252.98900000	3.61412857	1.36960310	1.17030043
MDEVN7	70	207.28300000	2.96118571	1.65304317	1.28570776

SET = 11

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	91	1754.88900000	19.28449451	1.21079574	1.10036164
BRIGHT5	91	2272.22000000	24.96945055	3.20140103	1.78924594
BRIGHT6	91	2558.88700000	28.11963736	6.97803934	2.64159788
BRIGHT7	91	2084.66500000	22.90840659	9.12385551	3.02057205
MINCON4	91	98.66300000	1.08420879	0.14188017	0.37666984
MINCON5	91	141.83200000	1.55859341	0.29958862	0.54734689
MINCON6	91	208.83200000	2.29485714	0.66608283	0.81613898
MINCON7	91	231.16800000	2.54030769	0.74157706	0.86114869
MDEVN4	91	91.53200000	1.00584615	0.15315360	0.39134844
MDEVN5	91	137.16000000	1.50725275	0.40260077	0.63450829
MDEVN6	91	191.90400000	2.10883516	0.67421056	0.82110326
MDEVN7	91	220.04700000	2.41809890	1.04746260	1.02345620

SET = 12

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	92	2117.22100000	23.01327174	3.37468295	1.83703101
BRIGHT5	92	2804.44300000	30.48307609	8.44975352	2.90684597
BRIGHT6	92	3204.77900000	34.83455435	8.16112366	2.85676804
BRIGHT7	92	2778.44100000	30.20044565	6.41471724	2.53272921
MINCON4	92	111.91600000	1.21647826	0.08868331	0.29779743
MINCON5	92	158.74900000	1.72553261	0.39355542	0.62733995
MINCON6	92	199.50500000	2.16853261	0.83089948	0.91153688
MINCON7	92	199.24700000	2.16572826	0.67820919	0.82353457
MDEVN4	92	108.42000000	1.17847826	0.09473232	0.30778616
MDEVN5	92	155.72900000	1.69270652	0.54416880	0.73767798
MDEVN6	92	192.71100000	2.09468478	0.83036011	0.91124097
MDEVN7	92	188.78500000	2.05201087	0.78983056	0.88872412

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SET = 13

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	143	3103.32700000	21.70158741	5.68157364	2.38360518
BRIGHT5	143	4048.77800000	28.31313287	11.24644796	3.35357242
BRIGHT6	143	4401.33500000	30.77856643	15.86360943	3.98291469
BRIGHT7	143	3655.22000000	25.56097902	16.87714105	4.10817977
MINCON4	143	192.24600000	1.34437762	0.16196018	0.40244277
MINCON5	143	256.66600000	1.79486713	0.27006009	0.51967306
MINCON6	143	293.82900000	2.05474825	0.37578442	0.61301257
MINCON7	143	260.33500000	1.82052448	0.32300387	0.56833430
MDEVN4	143	177.08500000	1.23835664	0.16459181	0.40569916
MDEVN5	143	235.30700000	1.64550350	0.34389939	0.58642936
MDEVN6	143	270.32500000	1.89038462	0.48150487	0.69390552
MDEVN7	143	253.42500000	1.77220280	0.43597243	0.66028208

SET = 14

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	150	3773.32900000	25.15552667	5.59361374	2.36508218
BRIGHT5	150	5121.21700000	34.14144667	13.16023151	3.62770334
BRIGHT6	150	5591.33300000	37.27555333	13.52363692	3.67744978
BRIGHT7	150	4621.10400000	30.80736000	11.21608207	3.34904196
MINCON4	150	232.58000000	1.55053333	0.28066832	0.52978139
MINCON5	150	363.58400000	2.42389333	0.49363803	0.70259379
MINCON6	150	384.91700000	2.56611333	0.88550954	0.94101516
MINCON7	150	334.08200000	2.22721333	0.51996617	0.72108680
MDEVN4	150	225.73100000	1.50487333	0.35413403	0.59509162
MDEVN5	150	344.86900000	2.29912667	0.65645002	0.81021603
MDEVN6	150	361.23500000	2.40823333	1.02429776	1.01207597
MDEVN7	150	310.34300000	2.06895333	0.54901984	0.74095873

SET = 15

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	96	2514.67200000	26.19450000	3.94203699	1.98545637
BRIGHT5	96	3452.99400000	35.96868750	9.07646893	3.01271786
BRIGHT6	96	3850.89000000	40.11343750	7.83047934	2.79829937
BRIGHT7	96	3295.44400000	34.32754167	6.44193629	2.53809698
MINCON4	96	113.74800000	1.18487500	0.39737849	0.63037964
MINCON5	96	186.16700000	1.93923958	0.65237639	0.80769821
MINCON6	96	212.83400000	2.21702083	0.41055246	0.64074368
MINCON7	96	177.41600000	1.84808333	0.50887496	0.71335472
MDEVN4	96	109.82700000	1.14403125	0.41278449	0.64248307
MDEVN5	96	177.06100000	1.84438542	0.80717462	0.89842897
MDEVN6	96	196.37100000	2.04553125	0.61605278	0.78489030
MDEVN7	96	173.47800000	1.80706250	0.53105732	0.72873680

SET = 16

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	93	2393.88900000	25.74074194	7.60572758	2.75784836
BRIGHT5	93	3257.44400000	35.02627957	19.20005290	4.38178650
BRIGHT6	93	3497.33600000	37.60576344	18.67713838	4.32170549
BRIGHT7	93	2741.89100000	29.48269892	13.88304895	3.72599637
MINCON4	93	181.25100000	1.94893548	0.85068539	0.92232607
MINCON5	93	263.66700000	2.83512903	1.80909042	1.34502432
MINCON6	93	314.91800000	3.38621505	2.88217441	1.69769680
MINCON7	93	283.99800000	3.05374194	1.97323024	1.40471714
MDEVN4	93	192.69200000	2.07195699	1.60004487	1.26492880
MDEVN5	93	283.03300000	3.04336559	3.44357345	1.85568679
MDEVN6	93	326.54800000	3.51126882	4.54244485	2.13130121
MDEVN7	93	281.13300000	3.02293548	3.26676489	1.80728108

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SET = 17

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	63	1181.66400000	18.75657143	2.82230938	1.67997303
BRIGHT5	63	1533.77800000	24.34568254	9.22620354	3.03746663
BRIGHT6	63	1632.55200000	25.91352381	16.18471635	4.02302328
BRIGHT7	63	1199.88700000	19.04582540	15.82907811	3.97857740
MINCON4	63	105.50100000	1.67461905	0.47690714	0.69058464
MINCON5	63	159.25000000	2.52777778	0.70035401	0.83687156
MINCON6	63	191.25000000	3.03571429	1.21017621	1.10008009
MINCON7	63	184.91700000	2.93519048	1.04847400	1.02395019
MDEVN4	63	106.22700000	1.68614286	0.63749922	0.79843548
MDEVN5	63	154.22300000	2.44798413	1.15747979	1.07586235
MDEVN6	63	189.43200000	3.00685714	2.01264603	1.41867756
MDEVN7	63	187.80000000	2.98095238	2.02850901	1.42425736

SET = 18

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	126	2547.21800000	20.21601587	0.92869310	0.96368724
BRIGHT5	126	3411.00200000	27.07144444	2.38535074	1.54445807
BRIGHT6	126	3731.99800000	29.61903175	3.48698257	1.86734640
BRIGHT7	126	2998.99900000	23.80157937	2.06307111	1.43633948
MINCON4	126	131.42100000	1.04302381	0.17466089	0.41792450
MINCON5	126	182.83400000	1.45106349	0.41236302	0.64215498
MINCON6	126	250.67100000	1.98945238	0.39321726	0.62707038
MINCON7	126	199.24900000	1.58134127	0.62764096	0.79223795
MDEVN4	126	126.18000000	1.00142857	0.18139189	0.42590127
MDEVN5	126	176.81900000	1.40332540	0.46776344	0.68393233
MDEVN6	126	226.88800000	1.80069841	0.54674552	0.73942243
MDEVN7	126	179.00600000	1.42068254	0.46276803	0.68027055

SET = 19

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	94	2362.89100000	25.13713830	1.58225950	1.25787897
BRIGHT5	94	3121.44600000	33.20687234	3.23602717	1.79889610
BRIGHT6	94	3370.22300000	35.85343617	2.81216840	1.67695212
BRIGHT7	94	2727.11400000	29.01185106	2.06419531	1.43673077
MINCON4	94	113.66500000	1.20920213	0.15227350	0.39022237
MINCON5	94	169.33400000	1.80142553	0.59273268	0.76989134
MINCON6	94	175.66600000	1.86878723	0.33434905	0.57822924
MINCON7	94	144.00000000	1.53191489	0.31200163	0.55857106
MDEVN4	94	104.47000000	1.11138298	0.13780237	0.37121741
MDEVN5	94	155.78100000	1.65724468	0.48340240	0.69527146
MDEVN6	94	153.35600000	1.63144681	0.25012599	0.50012598
MDEVN7	94	130.93900000	1.39296809	0.35564128	0.59635667

SET = 20

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	108	2742.89100000	25.39713889	2.23723068	1.49573750
BRIGHT5	108	3741.44500000	34.64300926	4.59301773	2.14313269
BRIGHT6	108	4099.11200000	37.95474074	4.95959608	2.22701506
BRIGHT7	108	3427.77600000	31.73866667	3.53665525	1.88059971
MINCON4	108	146.75100000	1.35880556	0.18647913	0.43183229
MINCON5	108	245.42100000	2.27241667	0.36496638	0.60412447
MINCON6	108	244.83400000	2.26698148	0.56910880	0.75439300
MINCON7	108	201.91500000	1.86958333	0.70353458	0.83876968
MDEVN4	108	131.50500000	1.21763889	0.11287193	0.33596419
MDEVN5	108	215.55100000	1.99584259	0.32449559	0.56964515
MDEVN6	108	213.48100000	1.97667593	0.56848030	0.75397632
MDEVN7	108	183.45500000	1.69865741	0.58568219	0.76529876

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SET = 21

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	64	1515.00100000	23.67189062	1.49898667	1.22433111
BRIGHT5	64	2096.77900000	32.76217187	4.37261608	2.09108012
BRIGHT6	64	2241.55800000	35.02434375	4.61232299	2.14763195
BRIGHT7	64	1846.55000000	28.85234375	2.47327356	1.57266448
MINCON4	64	72.33400000	1.13021875	0.06192567	0.24884868
MINCON5	64	98.08400000	1.53256250	0.26158784	0.51145658
MINCON6	64	114.33300000	1.78645312	0.38685914	0.62198002
MINCON7	64	75.83100000	1.18485937	0.15375555	0.39211676
MDEVN4	64	68.49400000	1.07021875	0.06786878	0.26051637
MDEVN5	64	96.66700000	1.51042187	0.39201666	0.62611234
MDEVN6	64	107.26300000	1.67598437	0.50116186	0.70792786
MDEVN7	64	75.80200000	1.18440625	0.17703485	0.42075509

SET = 22

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	51	1429.22600000	28.02403922	1.48999336	1.22065284
BRIGHT5	51	2048.44200000	40.16552941	4.16918837	2.04185905
BRIGHT6	51	2232.77700000	43.77994118	4.22527974	2.05554852
BRIGHT7	51	1829.00100000	35.86276471	4.14111186	2.03497220
MINCON4	51	55.58300000	1.08986275	0.25327880	0.50326812
MINCON5	51	88.66400000	1.73850980	0.43034541	0.65600718
MINCON6	51	100.41400000	1.96890196	0.30584809	0.55303534
MINCON7	51	80.25100000	1.57354902	0.43849797	0.66219179
MDEVN4	51	48.57000000	0.95235294	0.09442195	0.30728155
MDEVN5	51	77.58000000	1.52117647	0.36898839	0.60744414
MDEVN6	51	93.33300000	1.83005882	0.29131438	0.53973547
MDEVN7	51	74.07500000	1.45245098	0.30775297	0.55475488

SET = 23

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	111	2494.77600000	22.47545946	1.70279572	1.30491215
BRIGHT5	111	3307.44300000	29.79678378	3.38912043	1.84095639
BRIGHT6	111	3591.77900000	32.35836937	4.40517611	2.09885114
BRIGHT7	111	2877.44100000	25.92289189	2.95466097	1.71891273
MINCON4	111	176.08300000	1.58633333	0.30969402	0.55650159
MINCON5	111	227.00000000	2.04504505	1.10755712	1.05240540
MINCON6	111	220.24500000	1.98418919	1.09128065	1.04464379
MINCON7	111	220.16600000	1.98347748	0.54625338	0.73908956
MDEVN4	111	157.43000000	1.41828829	0.29752804	0.54546131
MDEVN5	111	201.80300000	1.81804505	1.00419121	1.00209341
MDEVN6	111	199.43200000	1.79668468	1.11364769	1.05529507
MDEVN7	111	186.34800000	1.67881081	0.51011175	0.71422108

SET = 24

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	131	2623.55700000	20.02715267	7.47648070	2.73431540
BRIGHT5	131	3158.33400000	24.10941985	27.74735617	5.26757593
BRIGHT6	131	5775.66600000	44.08905344	22.38868759	4.73166858
BRIGHT7	131	5802.66600000	44.29516031	58.92283977	7.67612140
MINCON4	131	180.42300000	1.37727481	0.39820949	0.63103842
MINCON5	131	284.16700000	2.16921374	1.00487046	1.00243227
MINCON6	131	319.91300000	2.44206397	0.57401231	0.75763600
MINCON7	131	429.58000000	3.27923664	1.93939812	1.39262275
MDEVN4	131	171.61200000	1.31001527	0.38496203	0.62045308
MDEVN5	131	284.39500000	2.17095420	1.36253960	1.16727871
MDEVN6	131	297.76100000	2.27298473	0.88766702	0.94216082
MDEVN7	131	410.54400000	3.13392366	2.60091718	1.61273593

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SET = 25

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	105	2739.77500000	26.09309524	2.64431293	1.62613435
BRIGHT5	105	3628.55300000	34.55764762	8.61951062	2.93590031
BRIGHT6	105	3848.00200000	36.64763810	14.10199587	3.75526242
BRIGHT7	105	2991.78000000	28.49314286	9.50658912	3.08327571
MINCON4	105	111.83900000	1.06513333	0.30521425	0.55246199
MINCON5	105	181.49700000	1.72854286	0.65758171	0.81091412
MINCON6	105	211.00200000	2.00954286	1.13930396	1.06738183
MINCON7	105	192.08200000	1.82935238	3.33132062	1.82519057
MDEVN4	105	101.09000000	0.96276190	0.24051649	0.49042481
MDEVN5	105	166.07500000	1.58166667	0.72150432	0.84941410
MDEVN6	105	193.78100000	1.84553333	1.19457510	1.09296619
MDEVN7	105	182.32000000	1.73638095	3.45553407	1.85890669

SET = 26

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	130	3483.66900000	26.79745385	0.76340532	0.87373069
BRIGHT5	130	4635.00100000	35.65385385	2.34700261	1.53199302
BRIGHT6	130	4877.89200000	37.52224615	2.78570941	1.66904446
BRIGHT7	130	3931.77500000	30.24442308	2.74514910	1.65684915
MINCON4	130	119.16500000	0.91665385	0.16598716	0.40741522
MINCON5	130	168.58700000	1.29682308	0.32534021	0.57038602
MINCON6	130	184.17200000	1.41670769	0.24007329	0.48997275
MINCON7	130	142.16700000	1.09359231	0.18246421	0.42715830
MDEVN4	130	108.30500000	0.83311538	0.10945523	0.33084020
MDEVN5	130	148.89300000	1.14533077	0.29523303	0.54335350
MDEVN6	130	153.55900000	1.18122308	0.22962532	0.47919236
MDEVN7	130	131.68500000	1.01296154	0.19870965	0.44576861

SET = 27

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	58	1419.33300000	24.47125862	2.15950107	1.46952410
BRIGHT5	58	1989.66500000	34.30456897	7.69833035	2.77458652
BRIGHT6	58	2380.22200000	41.03831034	6.24792187	2.49958434
BRIGHT7	58	2173.66500000	37.47698276	3.44170595	1.85518353
MINCON4	58	43.67000000	0.75293103	0.08113168	0.28483623
MINCON5	58	84.16700000	1.45115517	0.25173712	0.50173411
MINCON6	58	97.17100000	1.67536207	0.25704694	0.50699797
MINCON7	58	85.41800000	1.47272414	0.35927522	0.59939571
MDEVN4	58	38.45100000	0.66294828	0.04887023	0.22106611
MDEVN5	58	76.49300000	1.31884483	0.20818719	0.45627534
MDEVN6	58	86.98500000	1.49974138	0.20246627	0.44996252
MDEVN7	58	75.48300000	1.30143103	0.29365871	0.54190286

SET = 28

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	50	1192.00100000	23.84002000	2.09327039	1.44681387
BRIGHT5	50	1652.55700000	33.05114000	7.69502857	2.77399145
BRIGHT6	50	2006.89000000	40.13780000	6.39208102	2.52825652
BRIGHT7	50	1847.77500000	36.95550000	3.98918981	1.99729562
MINCON4	50	59.33000000	1.18660000	0.05968420	0.24430351
MINCON5	50	79.49900000	1.58998000	0.22104231	0.47015136
MINCON6	50	88.16500000	1.76330000	0.25638874	0.50634844
MINCON7	50	78.33100000	1.56662000	0.22366742	0.47293490
MDEVN4	50	56.51600000	1.13032000	0.05238410	0.22887573
MDEVN5	50	76.66700000	1.53334000	0.30230517	0.54982285
MDEVN6	50	80.79100000	1.61582000	0.27017921	0.51978766
MDEVN7	50	70.34300000	1.40686000	0.28889645	0.53749088

APPENDIX 2

Texture and Tone Variables of the Training Sets with Ratio Bands of LANDSAT Data

DISCRIMINANT ANALYSIS   SIMPLE STATISTICS

SET = 1

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	258	44579.55700000	172.78898062	3.81924701	1.95428939
BRIGHT5	258	60857.67000000	235.88244186	338.45936577	18.39726517
BRIGHT6	258	14113.88500000	54.70498062	56.20906558	7.49727054
BRIGHT7	258	37281.21900000	144.50084884	7.49230194	2.73720696
MINCCN4	258	788.08100000	3.05457752	0.99297022	0.99647891
MINCCN5	258	4244.66800000	16.45220155	655.93980442	25.61132180
MINCCN6	258	3317.16300000	12.85722093	16.62366157	4.07721247
MINCCN7	258	826.66800000	3.20413953	0.95096933	0.97517657
MDEVN4	258	602.14800000	2.33390698	0.57040026	0.75524847
MDEVN5	258	3819.15600000	14.80293023	586.74690742	24.22285919
MDEVN6	258	2667.13800000	10.33774419	11.65871099	3.41448547
MDEVN7	258	710.96400000	2.75567442	1.00495719	1.00247553

SET = 2

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	278	47439.55300000	170.64587410	8.62712362	2.93719656
BRIGHT5	278	61260.66700000	220.36211151	94.53781935	9.72305607
BRIGHT6	278	13938.65700000	50.13905396	1553.63705708	39.41620298
BRIGHT7	278	34807.66500000	125.20742806	16.17244762	4.02149818
MINCCN4	278	945.75500000	3.40199640	1.27517297	1.12923557
MINCCN5	278	2237.08500000	8.04706835	10.98785106	3.31479276
MINCCN6	278	13443.68000000	48.35856115	1507.30203903	38.82398793
MINCCN7	278	1025.58300000	3.68914748	1.85304922	1.36126750
MDEVN4	278	750.81200000	2.70076259	0.72887103	0.85373944
MDEVN5	278	1874.30600000	6.74210791	9.86474177	3.14081865
MDEVN6	278	12819.27600000	46.11250360	1514.33367058	38.91444039
MDEVN7	278	881.83200000	3.17205755	1.86980393	1.36740774

SET = 3

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	186	31430.45000000	168.98091398	3.70226513	1.92412711
BRIGHT5	186	43765.66900000	235.29929570	76.07415525	8.72204995
BRIGHT6	186	6257.45000000	33.64220430	32.90095452	5.73593537
BRIGHT7	186	25176.33300000	135.35662903	3.10340695	1.76164893
MINCCN4	186	524.49900000	2.81988710	0.75705763	0.87009058
MINCCN5	186	2145.92400000	11.53722581	287.90081373	16.96764019
MINCCN6	186	1907.24900000	10.25402688	10.48154083	3.23752078
MINCCN7	186	442.33100000	2.37812366	0.75782990	0.87053426
MDEVN4	186	417.38400000	2.24400000	0.50894268	0.71340219
MDEVN5	186	1713.77800000	9.21386022	182.47780732	13.50843467
MDEVN6	186	1495.35600000	8.03954839	5.94265597	2.43775634
MDEVN7	186	371.08003000	1.99505376	0.58207158	0.76293615

SET = 4

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	178	30523.00100000	171.47753371	7.82117591	2.79663654
BRIGHT5	178	39770.00200000	223.42697753	93.04507110	9.64598731
BRIGHT6	178	6455.55900000	36.26718539	920.52345613	30.34012947
BRIGHT7	178	22727.55000000	127.68286517	21.38572072	4.62446978
MINCCN4	178	582.75300000	3.27389326	1.19473701	1.09304026
MINCCN5	178	1247.00200000	7.00562921	15.72717757	3.96575057
MINCCN6	178	6038.00000000	33.92134831	1449.82267327	38.07653704
MINCCN7	178	655.08700000	3.68026404	5.65398991	2.37781200
MDEVN4	178	467.65700000	2.62728652	0.84267930	0.91797565
MDEVN5	178	1037.62700000	5.82936517	13.51354911	3.67607795
MDEVN6	178	5400.44100000	30.33955618	1223.40094775	34.97714894
MDEVN7	178	554.34100000	3.11427528	4.83871802	2.19970862

DISCRIMINANT ANALYSIS   SIMPLE STATISTICS

SET = 5

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	162	27542.77500000	170.01712963	3.86406324	1.96572207
BRIGHT5	162	37638.99800000	232.33949383	40.02750028	6.32672903
BRIGHT6	162	5085.67000000	31.39302469	56.97869462	7.54842332
BRIGHT7	162	21586.44600000	133.24966667	7.61098747	2.75880182
MINCON4	162	473.75100000	2.92438889	0.51212261	0.71562743
MINCON5	162	1032.75100000	6.37500617	12.51013396	3.53696677
MINCCN6	162	1698.16700000	10.48251235	5.64926344	2.37681792
MINCON7	162	506.33200000	3.12550617	2.61916113	1.61838226
MDEVN4	162	361.55200000	2.23180247	0.30916781	0.55602861
MDEVN5	162	851.97100000	5.25908025	12.56279525	3.54440337
MDEVN6	162	1403.04200000	8.66075309	4.76828155	2.18363952
MDEVN7	162	417.23100000	2.57550000	2.45208628	1.56591388

SET = 6

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	165	28208.55300000	170.96092727	1.80743292	1.34440802
BRIGHT5	165	32566.00100000	197.36970303	2249.74192656	47.43144449
BRIGHT6	165	11322.00100000	68.61818788	120.59978220	10.98179321
BRIGHT7	165	24397.11200000	147.86128485	20.19660217	4.49406299
MINCON4	165	482.25300000	2.92274545	0.76725423	0.87593049
MINCCN5	165	9402.41800000	56.98435152	1699.93290818	41.23024264
MINCCN6	165	2123.66600000	12.87070303	10.60892162	3.25713396
MINCON7	165	561.25000000	3.40151515	1.05818679	1.02868206
MDEVN4	165	378.49800000	2.29392727	0.50527759	0.71082881
MDEVN5	165	9849.52200000	59.69407273	1931.77916758	43.95200982
MDEVN6	165	1687.16300000	10.22523030	9.81735481	3.13326584
MDEVN7	165	476.69400000	2.88905455	1.35172914	1.16263887

SET = 7

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	183	30990.33800000	169.34610929	2.70056693	1.64334018
BRIGHT5	183	41781.67100000	228.31514208	620.65369516	24.91292225
BRIGHT6	183	11325.88400000	61.89007650	73.07104873	8.54816055
BRIGHT7	183	26454.77600000	144.56161749	5.71368461	2.39033149
MINCCN4	183	575.99800000	3.14753005	0.57205004	0.75633990
MINCCN5	183	5848.41600000	31.95855738	1337.97458389	36.57833490
MINCCN6	183	2198.75300000	12.01504372	16.20466843	4.02550226
MINCCN7	183	554.16800000	3.02824044	1.35239536	1.16292535
MDEVN4	183	439.99600000	2.40434973	0.35880279	0.59900149
MDEVN5	183	5427.99500000	29.66117486	1172.45246879	34.24109328
MDEVN6	183	1705.21100000	9.31809290	11.84418137	3.44153765
MDEVN7	183	449.33000000	2.45535519	1.08995971	1.04401136

SET = 8

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	111	19141.44500000	172.44545045	6.60727874	2.57046275
BRIGHT5	111	24883.66700000	224.17718018	747.01701391	27.33161199
BRIGHT6	111	7419.88800000	66.84583784	57.31313343	7.57054380
BRIGHT7	111	16467.55600000	148.35636036	4.93799903	2.22216089
MINCON4	111	431.25100000	3.88514414	0.93844434	0.96873337
MINCON5	111	4328.58300000	38.99624324	1472.72187926	38.37605867
MINCCN6	111	1825.91700000	16.44970270	62.05959827	7.87779146
MINCCN7	111	466.66600000	4.20419820	3.34896652	1.83001818
MDEVN4	111	362.31900000	3.26413514	0.69513021	0.83374469
MDEVN5	111	4030.53800000	36.31115315	1333.75085026	36.52055381
MDEVN6	111	1423.22900000	12.82188288	33.28512867	5.76932654
MDEVN7	111	381.33000000	3.43540541	2.28986437	1.51322978

DISCRIMINANT ANALYSIS   SIMPLE STATISTICS

SET = 9

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	74	12864.22100000	173.84082432	0.91662187	0.95740371
BRIGHT5	74	13592.22600000	183.67872973	2134.18557894	46.19724644
BRIGHT6	74	5289.89500000	71.48506757	67.72415576	8.22946874
BRIGHT7	74	11284.33700000	152.49104054	6.93977851	2.63434593
MINCON4	74	186.83400000	2.52478378	0.52691776	0.72589101
MINCON5	74	5657.08100000	76.44704054	1426.08221708	37.76350377
MINCON6	74	920.91200000	12.44475676	10.30990950	3.21090478
MINCON7	74	258.49900000	3.49322973	1.69337218	1.30129635
MDEVN4	74	142.24803000	1.92227027	0.20563927	0.45347466
MDEVN5	74	5843.00200000	78.95948649	1508.84730666	38.84388377
MDEVN6	74	771.72700000	10.42874324	11.64201482	3.41203969
MDEVN7	74	217.45400000	2.93856757	2.29687534	1.51554457

SET = 10

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	83	14690.33300000	176.99196386	3.66569172	1.91459962
BRIGHT5	83	15758.22400000	189.85812048	1767.08215235	42.03667628
BRIGHT6	83	6417.66700000	77.32128916	84.27092553	9.17991969
BRIGHT7	83	12872.88803000	155.09503614	10.25428716	3.20223159
MINCON4	83	295.08000000	3.55518072	0.78587874	0.88649802
MINCON5	83	6456.83300000	77.79316867	1956.56465378	44.23307195
MINCON6	83	1512.24600000	18.21983133	56.69119468	7.52935553
MINCON7	83	380.83300000	4.58834940	3.44829101	1.85695746
MDEVN4	83	242.36700000	2.92008434	0.54266030	0.73665480
MDEVN5	83	6025.37500000	72.59487952	1625.07668679	40.31223991
MDEVN6	83	1181.06000000	14.22963855	30.84709179	5.55401583
MDEVN7	83	303.43300000	3.65581928	2.23831759	1.49610080

SET = 11

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	196	34090.55800000	173.93141837	4.92940674	2.22022673
BRIGHT5	196	45925.88500000	234.31573980	104.43362084	10.21927692
BRIGHT6	196	8876.00100000	45.28571939	167.40120145	12.93836162
BRIGHT7	196	27807.66700000	141.87585204	24.81868838	4.98183584
MINCON4	196	646.59400000	3.29894898	0.84304021	0.91817221
MINCON5	196	3007.83500000	15.34609694	470.29446624	21.68627368
MINCON6	196	3290.24500000	16.78696429	51.67080306	7.18824061
MINCON7	196	793.75300000	4.04976020	1.96295659	1.40105553
MDEVN4	196	505.89700000	2.58110714	0.54782953	0.74015507
MDEVN5	196	2399.52503000	12.24247449	274.85967871	16.57889257
MDEVN6	196	2522.07200000	12.86771429	28.28926178	5.31876506
MDEVN7	196	687.24200000	3.50633673	1.83633655	1.35511496

SET = 12

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	143	24895.99800000	174.09788811	2.21258683	1.48747667
BRIGHT5	143	33777.11200000	236.20358042	432.78663341	20.80352454
BRIGHT6	143	6886.44700000	48.15697203	125.66505193	11.21004246
BRIGHT7	143	20705.88800000	144.79641958	9.21013681	3.03482072
MINCON4	143	514.25000000	3.59615385	0.79776217	0.89317533
MINCON5	143	2383.16300000	16.66547552	882.52522477	29.70732611
MINCON6	143	2148.33100000	15.02329371	40.42496343	6.35806287
MINCON7	143	464.91600000	3.25116084	1.26486178	1.12466074
MDEVN4	143	404.61600000	2.82948252	0.51995180	0.72107683
MDEVN5	143	2111.74800000	14.76746853	764.75690460	27.65423846
MDEVN6	143	1729.35800000	12.09341259	24.03002399	4.90204284
MDEVN7	143	387.21000000	2.70776224	0.87922486	0.93766991

DISCRIMINANT ANALYSIS   SIMPLE STATISTICS

SET = 13

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	150	25742.44700000	171.61631333	3.99324643	1.99831089
BRIGHT5	150	32981.45000000	219.87633333	1081.27742594	32.88278312
BRIGHT6	150	7283.55500000	48.55703333	47.01131282	6.85647962
BRIGHT7	150	21382.10900000	142.54739333	10.41093989	3.22659881
MINCON4	150	481.24800000	3.20832000	0.89003344	0.94341584
MINCON5	150	4895.17100000	32.63447333	1343.92901822	36.65963745
MINCON6	150	1825.08500000	12.16723333	21.81504711	4.67065810
MINCCN7	150	453.99700000	3.02664667	0.97420173	0.98701658
MDEVN4	150	379.55100000	2.53034000	0.47415529	0.68858935
MDEVN5	150	5086.63400000	33.91089333	1612.23786506	40.15268192
MDEVN6	150	1428.89100000	9.52594000	10.84053996	3.29249753
MDEVN7	150	386.51900000	2.57679333	1.03345119	1.01658801

SET = 14

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	93	15906.10800000	171.03341935	1.71596314	1.30994776
BRIGHT5	93	22140.22200000	238.06690323	41.76510959	6.46259310
BRIGHT6	93	4191.77400000	45.07283871	173.00041740	13.15296231
BRIGHT7	93	12934.77500000	139.08360215	9.36226142	3.05978127
MINCON4	93	249.83600000	2.68640860	1.06956383	1.03419719
MINCCN5	93	1037.75100000	11.15861290	284.17555889	16.85750749
MINCCN6	93	1727.83300000	18.57884946	352.76336380	18.78199574
MINCCN7	93	261.99700000	2.81717204	0.58782784	0.76669932
MDEVN4	93	184.51900000	1.98407527	0.42334770	0.65065175
MDEVN5	93	844.29600000	9.07845161	174.22378055	13.19938561
MDEVN6	93	1460.36500000	15.70284946	315.06589165	17.75009554
MDEVN7	93	233.08600000	2.50630108	0.51471284	0.71743491

SET = 15

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	154	26623.10800000	172.87732468	9.02623665	3.00436959
BRIGHT5	154	33579.66700000	218.04978571	647.92398425	25.45435099
BRIGHT6	154	10855.10400000	70.48768831	244.86443398	15.64814475
BRIGHT7	154	22953.66600000	149.04977922	39.23432089	6.26373059
MINCCN4	154	563.99000000	3.66227273	1.39344106	1.18044105
MINCON5	154	7127.99800000	46.28570130	1367.33310314	36.97746751
MINCCN6	154	2464.75100000	16.00487662	71.34352297	8.44650951
MINCCN7	154	699.66700000	4.54329221	3.00979444	1.73487592
MDEVN4	154	430.89000000	2.79798701	0.60735272	0.77932838
MDEVN5	154	6708.71000000	43.56305195	1260.16555869	35.49881067
MDEVN6	154	1976.27100000	12.83292857	45.66160533	6.75733715
MDEVN7	154	590.56900000	3.83486364	3.04482494	1.74494268

SET = 16

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	127	21909.44300000	172.51529921	4.10469704	2.02600519
BRIGHT5	127	30460.00500000	239.84255906	93.32396847	9.66043314
BRIGHT6	127	7264.23100000	57.19866929	77.51346425	8.80417312
BRIGHT7	127	18347.66800000	144.46982677	5.17028662	2.27382643
MINCON4	127	400.00900000	3.14967717	1.36317122	1.16754924
MINCCN5	127	1559.67000000	12.28086614	315.58822586	17.76480301
MINCON6	127	2366.15600000	18.63114961	180.34565762	13.42928359
MINCCN7	127	398.66900000	3.13912598	1.07340444	1.03605234
MDEVN4	127	334.54200000	2.63418898	0.76491650	0.87459505
MDEVN5	127	1285.60700000	10.12288976	235.50717694	15.34624309
MDEVN6	127	1742.61700000	13.72139370	58.43368091	7.64419263
MDEVN7	127	330.00300000	2.59844882	0.69281973	0.83235793

DISCRIMINANT ANALYSIS   SIMPLE STATISTICS

SET = 17

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	93	16124.66700000	173.38351613	3.43086877	1.85226045
BRIGHT5	93	21761.89100000	233.99882796	266.21076708	16.31596663
BRIGHT6	93	5072.77900000	54.54601075	71.41646732	8.45082643
BRIGHT7	93	13543.55400000	145.62961290	2.61075389	1.61578275
MINCCN4	93	292.41900000	3.14429032	1.01589430	1.00791582
MINCON5	93	2122.16800000	22.81901075	916.82643945	30.27914199
MINCCN6	93	1078.41900000	11.59590323	10.95645207	3.31005318
MINCCN7	93	282.58500000	3.03854839	0.55729625	0.74652277
MDEVN4	93	229.55300000	2.46831183	0.58277609	0.76339772
MDEVN5	93	1873.28600000	20.14286022	706.22995510	26.57498740
MDEVN6	93	875.83000000	9.41752688	8.39462753	2.89734836
MDEVN7	93	224.90900000	2.41837634	0.44200837	0.66483710

SET = 18

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	108	18494.11000000	171.24175926	4.88307461	2.20976800
BRIGHT5	108	25935.77900000	240.14610185	72.91962409	8.53929881
BRIGHT6	108	4905.33000000	45.41972222	52.88279198	7.27205555
BRIGHT7	108	15277.44400000	141.45781481	2.38205365	1.54339031
MINCCN4	108	403.75200000	3.73844444	0.97664100	0.98825148
MINCCN5	108	1294.08400000	11.98225926	285.73698459	16.90375652
MINCCN6	108	1358.75400000	12.58105556	16.99360646	4.12233022
MINCCN7	108	283.42100000	2.62426852	0.76729003	0.87595093
MDEVN4	108	306.09800000	2.83424074	0.59564663	0.77178147
MDEVN5	108	1022.39500000	9.46662037	185.13049592	13.60626679
MDEVN6	108	1008.74000000	9.34018519	7.98737376	2.82619422
MDEVN7	108	220.76400000	2.04411111	0.43438709	0.65908049

SET = 19

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	127	21502.89000000	169.31409449	3.51496780	1.87482474
BRIGHT5	127	30872.44500000	243.09011811	46.63828564	6.92922292
BRIGHT6	127	6300.33200000	49.60891339	29.20583981	5.40424276
BRIGHT7	127	17975.34100000	141.53811811	2.53022682	1.59066867
MINCON4	127	312.58500000	2.46129921	0.45082597	0.67143576
MINCON5	127	1130.84100000	8.90425984	220.86062181	14.86138021
MINCCN6	127	1368.66800000	10.77691339	10.12660378	3.18223251
MINCON7	127	268.42100000	2.11355118	0.41674725	0.64555964
MDEVN4	127	251.28100000	1.97859055	0.35263202	0.59382828
MDEVN5	127	926.34400000	7.29404724	149.98605995	12.24687960
MDEVN6	127	1042.22300000	8.20648031	7.02442236	2.65036269
MDEVN7	127	213.13700000	1.67824409	0.34467555	0.58709075

SET = 20

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	115	19876.33300000	172.83767826	3.93403508	1.98344021
BRIGHT5	115	27721.10800000	241.05311304	83.43229600	9.13412809
BRIGHT6	115	6535.44200000	56.82993043	38.69419070	6.22046547
BRIGHT7	115	16732.22000000	145.49756522	2.81596834	1.67808472
MINCON4	115	402.00100000	3.49566087	0.81600642	0.90333074
MINCCN5	115	1419.75000000	12.34565217	342.54158042	18.50787887
MINCON6	115	1341.99400000	11.66951304	12.56480330	3.54468663
MINCCN7	115	331.58500000	2.88334783	0.62338019	0.78954429
MDEVN4	115	306.54200000	2.66558261	0.49753003	0.70535809
MDEVN5	115	1124.99000000	9.78252174	201.87999097	14.20844787
MDEVN6	115	1041.94700000	9.06040870	7.94682779	2.81901185
MDEVN7	115	263.65700000	2.29266957	0.49602782	0.70429242

DISCRIMINANT ANALYSIS   SIMPLE STATISTICS

SET = 21

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	130	23453.10700000	180.40851538	37.24942576	6.10323076
BRIGHT5	130	22742.21800000	174.94013846	1713.08416055	41.38942088
BRIGHT6	130	13662.77900000	105.09830000	6677.84881660	81.71810581
BRIGHT7	130	14648.33100000	112.67946923	240.99370723	15.52397202
MINCON4	130	584.50200000	4.49616923	1.71735351	1.31047835
MINCON5	130	2012.24700000	15.47882308	49.42675443	7.03041638
MINCON6	130	6335.42000000	48.73400000	1773.17747938	42.10911397
MINCON7	130	782.50100000	6.01923846	7.51126877	2.74066940
MDEVN4	130	511.55100000	3.93500769	2.02283987	1.42226575
MDEVN5	130	2004.07000000	15.41592308	76.30632434	8.73534912
MDEVN6	130	6327.43000000	48.67253846	1867.88914549	43.21908312
MDEVN7	130	776.26800000	5.97129231	10.42106784	3.22816788

SET = 22

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	105	18193.22000000	173.26876190	3.83773876	1.95901474
BRIGHT5	105	22910.44400000	218.19470476	953.31369358	30.87577843
BRIGHT6	105	7031.55600000	66.96720000	92.39013041	9.61197849
BRIGHT7	105	15616.33500000	148.72700000	9.44438646	3.07317205
MINCON4	105	343.74800000	3.27379048	1.23116155	1.10957720
MINCON5	105	4783.75200000	45.55954286	1730.94944414	41.60468056
MINCON6	105	1521.83400000	14.49365714	129.98302623	11.40100988
MINCON7	105	374.66400000	3.56822857	9.51995883	3.08544305
MDEVN4	105	267.47900000	2.54741905	0.70997578	0.84260061
MDEVN5	105	4644.26900000	44.23113333	1620.06666571	40.25005175
MDEVN6	105	1156.06900000	11.01018095	93.08282940	9.64794431
MDEVN7	105	304.91700000	2.90397143	9.39891166	3.06576445

SET = 23

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	63	10957.22500000	173.92420635	1.21066852	1.10030383
BRIGHT5	63	14806.11500000	235.01769841	394.44379370	19.86060910
BRIGHT6	63	3614.22100000	57.36858730	12.45506334	3.52917318
BRIGHT7	63	9309.77500000	147.77420635	0.54443397	0.73785769
MINCON4	63	154.75200000	2.45638095	0.74109634	0.86086952
MINCON5	63	1698.41700000	26.95900000	1554.78877852	39.43081002
MINCON6	63	593.58100000	9.42192063	9.42127220	3.06940910
MINCON7	63	121.66700000	1.93122222	0.56221579	0.74981050
MDEVN4	63	137.21200000	2.17796825	0.48461348	0.69614186
MDEVN5	63	1427.03700000	22.65138095	858.21732101	29.29534641
MDEVN6	63	449.53000000	7.13539683	6.35665918	2.52124159
MDEVN7	63	104.74100000	1.66255556	0.40516803	0.63652810

SET = 24

VARIABLE	N	SUM	MEAN	VARIANCE	STANDARD DEVIATION
BRIGHT4	57	9787.66400000	171.71340351	0.89151792	0.94420227
BRIGHT5	57	12786.67100000	224.32756140	616.79464961	24.83535081
BRIGHT6	57	2923.88800000	51.29628070	15.47244967	3.93350349
BRIGHT7	57	8267.00200000	145.03512281	1.60359982	1.26633322
MINCON4	57	158.66600000	2.78361404	0.74926963	0.86560362
MINCON5	57	2583.41600000	45.32308772	2124.41981287	46.09142884
MINCON6	57	587.00000000	10.29824561	5.66341262	2.37979256
MINCON7	57	131.58400000	2.30849123	0.56069533	0.74879592
MDEVN4	57	122.00000000	2.14035088	0.41161470	0.64157205
MDEVN5	57	2210.41900000	38.77928070	1279.13533660	35.76500156
MDEVN6	57	448.54400000	7.86919298	3.98973209	1.99743137
MDEVN7	57	107.55700000	1.88696491	0.32702743	0.57186312